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EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE USING DEEP LEARNING APPROACH

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ABSTRACT

Alzheimer's disease (AD) is a neurological ailment that progresses over time and is characterized by behavioral changes and cognitive decline that eventually affect every day functional tasks. Although there is no known treatment for the condition, some drugs and therapies can help temporarily manage symptoms, and the disorder can progress at different rates. Neuronal atrophy, amyloid deposition, and cognitive, behavioral, and mental problems are the main hallmarks. It moves slowly, destroys memory cells, and impairs a person's ability to think. In order to diagnose Alzheimer's disease early utilizing multimodal images, this paper presents a hybrid deep learning approach using Transfer learning and optimization. You have a better chance of benefiting from treatment if you receive an early diagnosis of Alzheimer's disease. Images from an MRI scan are utilized in this work. Repeated scans can reveal how the brain evolves over time. The brain's blood arteries are likewise depicted in great detail by MRI. They were able to accurately identify the risk of Alzheimer's disease using deep learning, which has already been demonstrated to reliably diagnose a number of diseases in data from high-quality brain magnetic resonance imaging (MRIs) obtained in a controlled study context. To save time and help patients with this illness, radiologists, doctors, and caregivers should work together to create the best prediction and detection techniques. The Kaggle website provided the dataset. There are four categories of MRI images: mild, extremely mild, moderate, and non-demented. This task will involve pre-processing, transfer learning, feature selection (using an evolutionary approach), and classification. Filter and remove noise during preprocessing. To classify data, CNN, DBN, LSTM, and Bi-LSTM are employed. Performance is improved via feature selection and transfer learning. This method enhances clinical tests that can quickly identify AD patients and shorten the research process. Enhance performance one by one to raise the accuracy value for using MRI pictures to identify AD patients.

Keywords: Segmentation, CNN, DBN, LSTM, Bi-LSTM

1. INTRODUCTION

Despite recent advances in AD research, there is still no cure for AD patients at this time. In order to quickly determine the patient's stage, MRI pictures of AD patients should be used in conjunction with computer technologies. Despite the significant advancements in diagnostic imaging technologies, pathologists still grade and stage AD using a visual examination of histological samples under a microscope. One of the pathologist's main techniques when examining a histological slide as part of the diagnosing process is pattern recognition. Pattern recognition is the understanding that the MRI pictures of the AD match a known pattern of the illness. In actuality, today's pathological diagnosis relies on pathologists' expert opinions.

In order to construct an accurate MRI image of an AD patient that can be applied in a practical situation, classification techniques are reviewed in this chapter. The data presented in this chapter also demonstrate how the research's objectives can be accomplished in a methodical way. This framework covers four classes, each of which has an anticipated delivery or discovery. Each phase contains goals and objectives that are quite specific. Recognizing the series of events that take place at each stage of the framework is also straightforward. The set of actions can be controlled and monitored at the conclusion of each step, and the goals can be thoroughly specified. Consistently taking into account the methodology, required tools, and software is a must for the development of this framework.

Recently, it has become possible to apply deep learning techniques and computerized image analysis to digital tissue AD. In pathology labs, the usage of computer-aided detection (CAD)/computer-aided diagnosis (CADx) systems has increased significantly due to reasons like cheaper storage devices, large improvements in available computer power, and major developments in image analysis methods. A number of technologies have developed for the detection, diagnosis, and prognosis prediction of illnesses to enhance the perspective of the human expert, the pathologist. Recent developments in image processing and segmentation methods have paved the way for the creation of CAD/CADx systems that can assist pathologists in making accurate, consistent, and productive diagnoses while freeing up specialists to concentrate on cases that are more challenging to diagnose.

2. PROBLEM STATEMENT

Alzheimer's patients are especially prone to depression in the early stages of the illness. Memory loss is severe and decision-making gets harder as the disease progresses. The brain shrinks as a result of AD, and brain cells finally pass away. These changes, which include a steady decline in memory, thinking, behavior, and social skills, impact a person's capacity to operate. Identifying the stage of an AD patient's illness is equally challenging. Although the classification function for the MRI images and feature selection had the highest accuracy, transfer learning performance is used to identify this patient case. In pathology, it shortens the search time for AD patients and uses DL technology to find them. The most accurate model found in earlier studies must be used to gain a better understanding of additional AD MRI image datasets.

3. RELATED WORKS

Analysis of the patient's brain's MRI pictures is the main diagnostic technique. Our method employs the aVGG16 architecture, which has been trained on a number of these MRI images. The class of Alzheimer's stage to which the MRI image belongs is predicted by a newly trained model, together with conditional probabilities (between 0-1) for each class [1]. The study of prodromal stages of neurodegenerative disease, or mild cognitive impairment, which occur before the full-blown dementia condition, became more popular in the 2000s. The use of imaging and other indicators to identify preclinical disease before the onset of serious cognitive loss has increased during the past ten years. The use of imaging and other indicators to identify preclinical disease before the onset of serious cognitive loss has increased over the past ten years [2].

A person with dementia is unable to live a completely functioning and independent life because of impairment in a number of cognitive domains [3]. Hippocampus and brain volume are included in the region that a brain MRI may identify. Hippocampus and brain volume are included in the region that a brain MRI may identify [4]. The history of AD is a compilation of information from publications that were looked for on Google Scholar. Only papers published between 2008 and 2019 were chosen, and only the most recent publications were taken into account. Our study concentrated on datasets used to analyze moderate cognitive impairment (MCI), which is the precursor to AD and AD [5].The features on the fMRI data are acquired by using the PCANet network to the investigation of the connections between brain functions. Next, the features from the sMRI and fMRI are fused using kernel canonical correlation analysis (KCCA). The first diagnosis of AD will benefit greatly from the adoption of automated algorithms that can distinguish between problematic and normal patients based on their magnetic resonance imaging (MRI) scans (i.e., no previous hypotheses are required) [6].

Magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), and diffusion tensor imaging are the imaging modalities. 4) Amyloid-PET, and 5) Positron emission tomography [7]. In the first technique, 2D and 3D convolution-based simple CNN architectures are used to process structural brain scans in 2D and 3D from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. The second approach makes use of the VGG19 model and other pre-trained medical picture classification models by employing the transfer learning principle [8].

When you compare the performance of a CNN deep learning model and a hybrid model, which combines VGG19 and additional layers, you can see that the hybrid model performs more effectively at identifying and categorizing the various stages of Alzheimer's [9]. The network model's performance can be enhanced by using each of the weighted loss, transfer learning, and mish activation functions, which can lead to an increase in the accuracy of the AD and CN classes [10]. The median filter lessens random noise while maintaining an image's edges. The median filter also reduces random noise while maintaining the boundaries of an image. Each pixel's value is fixed at the median of the pixels closest to it. A filter is used to eliminate these disturbances [11]. Both ROI and HOG features were extracted from processed MRI images and mapped onto the ROI space to make them comparable and to support the higher similarity value. A support vector machine is trained on both actual ROI data and mapped HOG characteristics for AD diagnosis [12]. In this study, we compared various models and datasets to enhance MRI image-based early AD identification. We may conclude that the VGG-16 model performed better than DenseNet-169 and Resnet-50 by analyzing the testing dataset model performances [13].

Because of their sensitivity, the difficulty of executing operations, and the high expenses, disorders affecting the brain are among the most challenging diseases to treat. Contrarily, since the surgery's outcomes are not certain to be successful, the operation itself need not be successful. Alzheimer's disease, which affects adults and causes varied degrees of memory loss and knowledge forgetting, is one of the most prevalent diseases that affect the brain [14]. The most recent advances in machine learning have been revealed, including the types of data used and how well early-stage Alzheimer's may be diagnosed using machine learning algorithms. Prediction accuracy is inevitably improved by machine learning, especially when compared to conventional statistical techniques [15]. The primary objectives of doctors are met by automatic early identification of AD. For the early detection of AD patients, an automated framework and classification system for AD based on MRI scans are essential. For the purpose of using MRI data to predict early AD, a hybrid strategy is suggested. 512 MRI scans and 112 PET images were used as the training datasets in this work [16]. The ensemble learners on ML methods and the ANN model were used to test and analyze the suggested scheme. All other defined classifiers are outperformed by the ANN model [17]. The study of computational methods for improving performance on a particular task through the process of learning is known as machine learning. Researchers need to understand how these brain nerves arise in order to find a cure or aversion; they need to know more than just that there are protein abnormalities from the norm. Although abnormal protein bundles in brain tissue are a distinctive feature of Alzheimer's disease, it is unclear what causes the condition [18].

They developed a multifold Bayesian Kernalization technique, which can more accurately distinguish AD from NC, however they discovered disappointing outcomes in the diagnosis of MCI-converter. For classification, regression, and other purposes, an SVM's hyperplane produced in a high- or infinite-dimensional space may be used. SVMs are typically used to address pattern classification challenges when you have a small number of training samples because of their capacity to reduce generalization mistakes. [19]. LS-SVM is an extension to SVM that finds a training model for classification and solves linear equations. SVMs come in two varieties: one for linear equations and the other for quadratic equations. In order to use LS-SVM, you only need to solve a few linear equations to comprehend how it functions differently from SVM. The LS-SVM just requires a few parameters to function. The radial basis function (RBF) kernel is used by SVM [20]. used the anticipated increase in the price of treating an AD patient. As the sixth leading cause of mortality in the US, AD has surpassed cancer. As a result, certain computer-assisted procedures are required for the accurate and prompt diagnosis of this illness [21]. Prior studies have combined machine learning and deep learning algorithms with MRI-based classification techniques. After 23, 30, and 39 epochs, respectively, the training AUC performances for each of the models DenseNet-169, VGG-16, and Resnet-50 were 0.98, 0.95, and 0.875 [22]. Age is the primary risk factor, with most instances affecting people over 65, while genetic predisposition is the secondary risk factor [23]. The SFG supports higher cognitive processes, especially working memory. Short-term memory and occasionally episodic memory are the main functions of the hippocampal area [24]. used functional connection matrices and stacked automated encoders to distinguish between migraine sufferers and healthy individuals [25]

4. DATASET DESCRIPTIONS

The data sets are crucial since they are used to train the model to take the necessary actions. The majority of the data needed to train the model and the data set are also divided into test data. The method is run using the suggested system on datasets related to AD that were downloaded from Kaggle [2]. There are MRI images in the data. Four classes of photos are present in the data, both in the training set and the testing set: There are four levels of mental illness: very mild, mild, moderate, and demented.

DATASET ⇨ IMAGES (6040)			
Train data		**Test data**	
Very Mild Demented	1792	Very Mild Demented	448
Non-demented	2560	Non-demented	12
Moderate Demented	52	Moderate Demented	640
Mild Demented	717	Mild Demented	179
Total	**5121**	Total	**919**

5. METHODOLOGY

The method begins with a classification technique that divides the dataset into train data and test data. Next, pre-processing is done to remove noise from the input image and apply filters to the data. Use feature selection (Evolution Algorithm) and transfer learning with classified data to improve performance. The proposed work shows four classes of the MRI pictures for Alzheimer's disease that are displayed in figure 3.1. The most accurate classification algorithm operates with transfer learning, which boosts accuracy. Value transfer learning uses an efficient evolutionary approach for greater accuracy.

Finally, four categories—Very mild demented, Mild demented, Moderately demented, and Non-demented—were created from the photographs of people with Alzheimer's disease. This was done to determine the diagnoses' stage.

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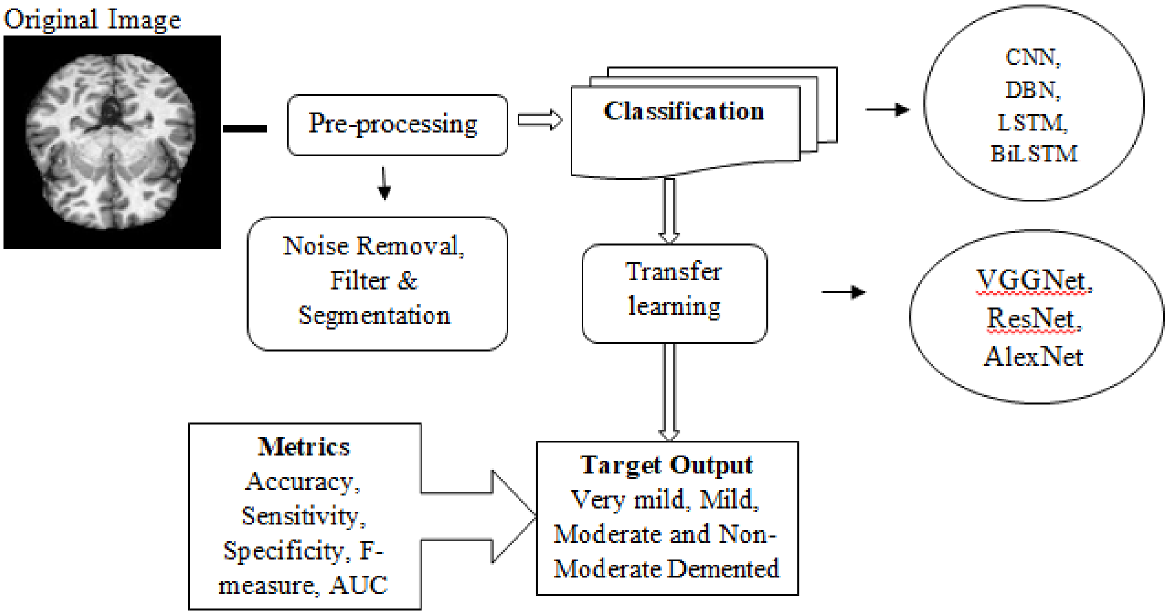


Figure 5.1 Workflow of Alzheimer's disease classification

5.1 Pre-processing

The term "image pre-processing" refers to operations on images at the most basic abstraction level. If entropy is a measure of information, then these actions diminish rather than increase the information content of the image. Before developing the model, most ML engineers devote a significant amount of effort to data pre-processing, often known as data purification. Outlier detection, missing value treatments, and removing undesired or noisy data are a few examples of data pre-processing. To more effectively classify data, data pre-processing techniques including normalization, feature extraction, and dimension reduction are required. To enhance the effectiveness of the classifier, pre-processing aims to identify the most informative set of characteristics.

Differences in picture quality can significantly affect how an image is classified. These variations are caused by a variety of factors, such as inconsistent conditions during the production of tissue slices or picture collecting. Appropriate pre-processing techniques, like color normalization to minimize staining variations, spatial filtering to highlight major image structure, denoising to reduce image noise, and enhancement to maximize contrast between objects of interest and background, could all contribute to some reduction in variations.

5.1.1 Image Filtering Technique

In an image processing system, the first and most important stage is called picture smoothing, which involves filtering the image to remove noise, clean up the edges, and improve quality. In order to produce less pixelated and clearer images, smoothing is an image processing technique used to lower the noise in an image. Low pass linear filters are the foundation for most smoothing methods. It is mostly based on the middle (median) value approach or the input image averaging technique. Three different sorts of filters were implemented in the system to achieve this: Gaussian, Wiener, and the median filters.

5.1.2 Noise

Similar undesirable behaviors within the data that have a low signal-to-noise ratio are referred to as noise. Data basically equals signal plus noise. While a small portion of data noise is irreducible, mot can be avoided by comprehending and addressing its causes. Humans have a tendency to misuse tools and make mistakes when gathering data, therefore there will always be some errors in the data. In a dataset, this inaccuracy is referred to as noise. The forecast of any important information can be greatly impacted by noisy data.

5.2 Segmentation

A critical stage of image processing is image segmentation. When dealing with medical images, it becomes much more visually important because choices must be taken before and after surgery to start and speed up the recovery process. In order to achieve the highest level of accuracy, abnormal tissue development is identified using computer assistance. The manual segmentation of these defective tissues is superior to the high-speed computing tools of today, which allow us to track the volume and location of undesired tissues.

5.2.1 Segmentation Using Fuzzy C-Means Clustering

The fuzzy c-mean method is a popular picture segmentation algorithm that divides the image space into discrete cluster parts with similar pixel values. It is frequently employed in picture segmentation and pattern recognition. Fuzzy clustering is the most effective clustering technique for segmenting medical images. In that it is a fuzzy variation of the k-means algorithm, the fuzzy c-means (FCM) algorithm is related to it. Data items may belong to multiple clusters to varying degrees based on membership in this clustering approach [77]. The method uses an iterative clustering methodology to obtain the optimal c partition by minimizing the weighted within group sum of squared error objective function.

The image space is divided into cluster portions via the fuzzy c-mean technique using similar pixel values. It's often used in applications like image segmentation and pattern identification. The best clustering technique for medical image segmentation is fuzzy clustering. A fuzzy version of the k-means algorithm is fuzzy c-means (FCM). It is a clustering approach that allows data objects to have varying degrees of membership in various groups. The process is an iterative clustering method that finds the optimal c partition by minimizing the weighted within group sum of squared error objective function.

5.2.2 Segmentation Using K-Means Clustering

Data are grouped using the K Means clustering method. Unsupervised clustering techniques do not employ tagged data. Depending on how similar a set of data is, it can be used to identify different classes or clusters within it. The similarities between data points from different groups and those from the same group are greater. K-means clustering is one of the most popular clustering methods. K stands for the number of clusters. K- The clustering method known as K Means. Since clustering algorithms don't use labelled data, they are unsupervised algorithms. Depending on how similar a set of data is, it can be used to identify different classes or clusters within it. Comparable data points are more similar than those in other groupings. A well-liked clustering algorithm is K-means clustering. The letter indicates how many clusters are present.

5.2.3 Watershed Segmentation Using Gradients

A grayscale image can be preprocessed with gradient magnitude before being segmented with the Watershed transformation. Dilation and erosion can be used in conjunction with image subtraction to produce the Morphological Gradient image with the smoothed image. Parts of an image might thicken and thin due to erosion and dilation. In Watershed Segmentation, the opening and closing steps are used to introduce the Morphological Gradient-based Watershed Segmentation. The gradient image is then reorganized using reconstruction techniques, which keep a group of high-value gradient pixels while separating out a few low-value gradient pixels.As a result, a more effective technique that employs gradients is used to partially eliminate over-segmentation in order to reassemble images..

5.3 Classification

A supervised machine learning technique called classification asks the model to guess the appropriate label for some input data. When performing classification, the model is fully trained using the training data, evaluated using test data, and then used to make predictions on fresh, unused data. Although they both fall under the umbrella of supervised learning, classification and regression are not the same. In cases where the target variable is discrete, the prediction task is a classification. Finding the underlying meaning of a piece of text is an application. In machine learning, a classification problem is one where a class label is anticipated for a particular example of input data. The following are some categorization issues: Give an illustration and say whether or not it is spam. Determine whether a handwritten character belongs with the known characters.

5.3.1 Convolutional Neural Network (CNN)

A deep learning system known as a convolutional neural network (CNN) is particularly effective at processing and recognizing images. Convolutional layers, pooling layers, and completely connected layers are among the layers that make up this structure. The key part of a CNN is its convolutional layers, where filters are used to extract characteristics like edges, textures, and forms from the input image. The output of the convolutional layers is then sent through pooling layers, which are employed to down-sample the feature maps and retain the most crucial data while lowering the spatial dimensions. One or more fully connected layers are then applied to the output of the pooling layers in order to forecast or categorize the image.

- **Step 1:** The convolutional layer that performs the convolution operation is fed the pixels from the image.
- **Step 2:** A convolved map is the outcome.
- **Step 3:** To create a corrected feature map, the convolved map is put to a ReLU function.
- **Step 4:** To locate the features, the image is processed using several convolutions and ReLU layers.
- **Step 5:** To identify specific areas of the image, several pooling layers with different filters are utilized. Step 6: To obtain the final output, the pooled feature map is flattened and supplied to a fully connected layer.

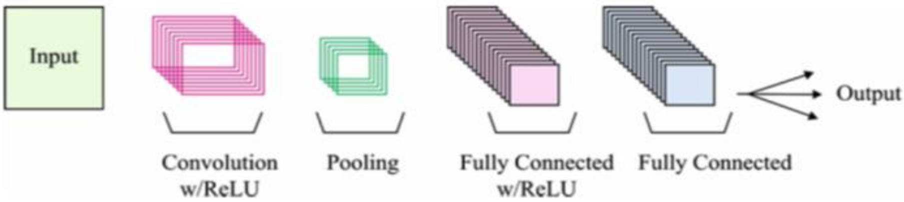


Figure 5.2 Convolutional Neural Network

The different layers of a CNN

A convolutional neural network has four different types of layers: the convolutional layer, the pooling layer, the ReLU correction layer, and the fully connected layer.

i) Convolutional Layer

A feed-forward neural network called convolutional network analyses visual images by processing data in a grid-like architecture. It is also referred to as a ConvNet. To find and categorize items in an image, a convolutional neural network is employed. The process of removing useful elements from an image begins with this. Multiple filters work together to perform the convolution operation in a convolution layer. Each image can be thought of as a matrix of pixel values.

ii) ReLU Layer

The rectified linear unit is referred to as ReLU. The next step is to transfer the feature maps to a ReLU layer after they have been retrieved. ReLU executes an operation element-by-element, setting all the negative pixels to 0. It gives the network nonlinearity, and the result is a rectified feature map.

iii) Pooling Layer

The down sampling process of pooling lowers the feature map's dimensionality. To create a pooled feature map, the rectified feature map is now passed through a layer of pooling. To distinguish various portions of the image, such as edges, corners, bodies, feathers, eyes, and beak, the pooling layer employs a variety of filters.

iv) Fully-connected Layer

Every neuron in one layer communicates with every other layer's neuron through fully connected layers. Similar to a conventional multilayer perceptron neural network (MLP), it is the same. To categorize the photos, the flattened matrix passes through a fully linked layer.

5.3.2 Deep Believe Network (DBN)

In order to address the issues with typical neural networks training in deep layered networks, such as slow learning, becoming stuck in local minima owing to poor parameter selection, and needing a large amount of training datasets, deep belief networks (DBNs) were developed. A deep belief network (DBN) is a type of deep neural network used in deep learning. It is made up of numerous layers of latent variables (also known as "hidden units"), with connections between the layers but not between the units within each layer. Unsupervised training on a set of instances enables a DBN to develop the ability to probabilistically recreate its inputs. After that, the layers serve as feature detectors. A DBN can be further taught under supervision to perform categorization after this learning phase. One of the first successful deep learning algorithms was created as a result of the discovery that DBNs may be trained greedily, one layer at a time. DBNs can be used in a variety of appealing ways in practical scenarios and applications. The information processing and distributed communication nodes in biological systems served as the inspiration for artificial neural networks (ANNs). ANNs and biological brains differ in a number of ways. In particular, artificial neural networks frequently have a static, symbolic nature, whereas the organic brains of the majority of living things have a dynamic, malleable, analog nature. Each degree of deep learning learns how to change the incoming data into a tad more abstract and composite representation. The initial representational layer in an image recognition application may abstract the pixels and encode edges from the raw input, which may be a matrix of pixels.

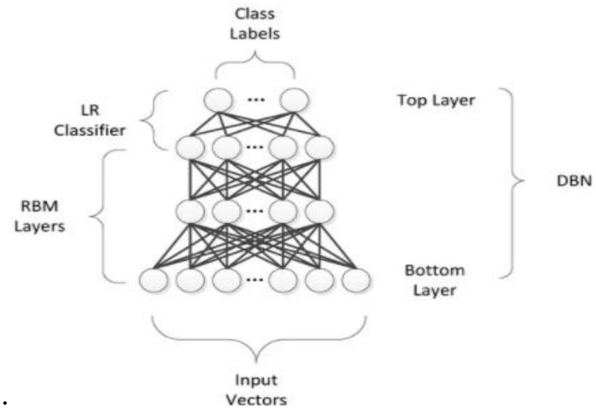


Figure 5.3 Deep Believe Network

In DBN, there are several hidden layers between input layer and output layer.

5.3.3 Long Short-Term Memory (LSTM)

Recurrent neural networks include long short-term memory. The output from the previous phase is sent into the current step of an RNN as input. Hochreiter & Schmid Huber created LSTM. It addressed the issue of long-term RNN dependency, in which the RNN can predict words from current data but cannot predict words held in long-term memory. RNN's performance becomes less effective as the gap length increases. By default, LSTM can save the data for a very long time. It is utilized for time-series data processing, forecasting, and classification. Recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) are especially made to handle sequential data, including time series, speech, and text. LSTM networks are particularly suited for applications like language translation, speech recognition, and time series forecasting because they can learn long-term dependencies in sequential data. A cell, an input gate, an output gate, and a forget gate make up a typical LSTM unit. Three gates regulate the information flow into and out of the cell, and the cell retains values for arbitrary time periods. Because it enables the learning of even more parameters, the LSTM cell increases long-term memory in a way that improves performance.

5.3.4 BiLSTM

A bidirectional LSTM, often known as a biLSTM, is a sequence processing model that consists of two LSTMs, one of which receives input forward and the other of which receives it backward. With the help of BiLSTMs, the network has access to more information, which benefits the algorithm's context. A bidirectional LSTM differs from a conventional LSTM in that our input flows in two directions. We may make input flow in one way, either backwards or forward, using the standard LSTM. However, with bi-directional input, we can maintain both future and historical information by allowing input to flow in both directions.

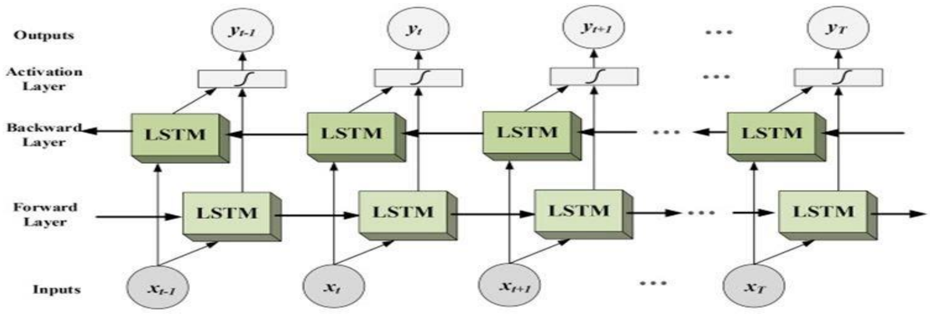


Figure 5.4 Work flow of Bi-LSTM

The information flow from backward and forward levels is depicted in the diagram. Wherever the need for sequence-to-sequence tasks exists, BI-LSTM is typically used. This type of network can be applied to forecasting models, speech recognition systems, and text categorization systems.

5.4 Transfer Learning

Transfer learning (TL) is a machine learning (ML) research subject that focuses on using information learned while completing one job to complete a related one. Transfer learning's fundamental tenet is straightforward: take a model that has been trained on a sizable dataset and apply its knowledge to a smaller dataset. With a CNN, we only train the final few layers that make predictions for object recognition and freeze the network's early convolutional layers. Due to the enormous amount of computational power needed, transfer learning is primarily used in computer vision and natural language processing tasks like sentiment analysis. Transfer learning is more of a "design methodology" within the field of active learning than it is a machine learning technology. Res Net, VGG Net, and Alex Net are employed in this.

5.4.1 ResNet

The most often mentioned neural network of the twenty-first century, a residual neural network, was utilized to win the ImageNet 2015 competition.A deep learning model called Residual Network (ResNet) is applied in computer vision applications. It is an architecture for a convolutional neural network (CNN) that can accommodate hundreds or even thousands of convolutional layers. Artificial neural networks (ANNs) include residual neural networks (ResNet). It is a gateless or open-gated variation of the HighwayNet, which was the first functionally complete, extremely deep feedforward neural network with hundreds of layers—much deeper than earlier neural networks. Some layers can be bypassed using skip connections or shortcuts (HighwayNets may also learn the skip weights through an additional weight matrix for their gates).

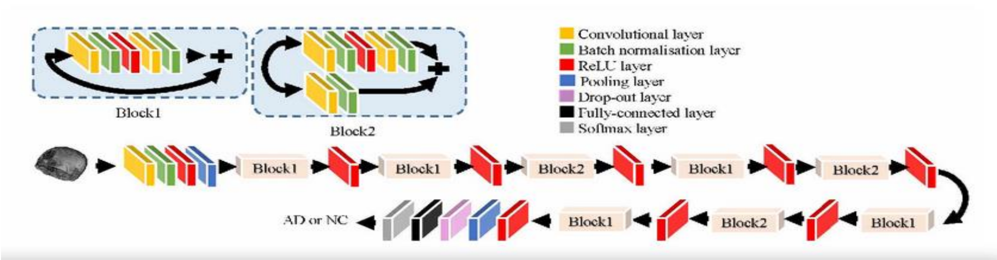


Figure 5.5 ResNet

Typical ResNet models are implemented with batch normalization in between double- or triple-layer skips that contain ReLU nonlinearities. DenseNets are models that have numerous parallel skips. A non-residual network is referred to as a plain network while discussing residual neural networks. By skipping layers during early training, the network is effectively simplified and uses fewer layers. As it learns the feature space, the network then gradually restores the skipped layers. When all layers are expanded toward the end of training, it stays closer to the manifold and thus picks up information more quickly. A neural network that has no leftover components scours more of the feature space. This increases its susceptibility to disturbances that force it to depart from the manifold, necessitating additional training data to recover.

5.4.2 VGGNet

The University of Oxford's Karen Simonyan and Andrew Zisserman proposed the Convolutional Neural Network architecture known as VGGNet in 2014. The main topic of this research is the impact of convolutional neural network depth on accuracy. Innovative object identification models are built using the VGG architecture. The VGGNet, created as a deep neural network, outperforms benchmarks on a variety of tasks and datasets outside of ImageNet. It is also remains one of the most often used image recognition architectures today. Traditional convolutional neural network architecture is the VGG. It was based on a study of how to make these networks deeper. The network makes use of tiny 3 by 3 filters. The network is distinguished by its simplicity elsewhere; the only additional elements are pooling layers and a fully linked layer.

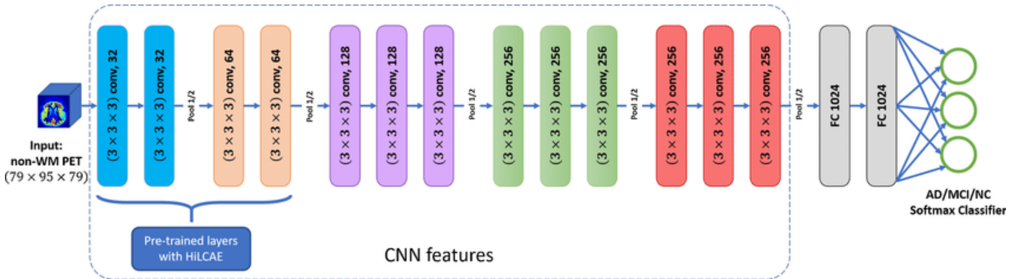


Figure 5.6 Visual Geometry Group (VGG)

VGG16 is an object identification and classification method that has a 92.7% accuracy rate when classifying 1000 photos into 1000 different categories. It is a well-liked technique for classifying images and is simple to employ with transfer learning. VGG-16 is a deep convolutional neural network made up of 16 layers that are regularly concatenated into 33 convolutional layers and 22 pooling layers. VGG-16 has a remarkable capacity to extract features, which enables it to perform well in picture categorization. The Oxford-based Visual Geometry Group created the convolutional neural network architecture known as VGG16, commonly known as OxfordNet. 2014's ILSVR (ImageNet) competition was won using it.

5.4.3 AlexNet

Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton created AlexNet, a convolutional neural network (CNN) architecture, in 2012. It helped establish CNNs as a potent image recognition technique as it was the first CNN to win the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a significant image recognition competition. AlexNet is made up of fully connected layers on top of a number of convolutional and pooling layers. Three pooling layers, three fully connected layers, and five convolutional layers make up the architecture. The input image is processed by the first two convolutional layers using 96 filters and a 1111 kernel. The third and fourth convolutional layers employ 256 filters and a 55 kernel. The fifth convolutional layer employs 384 filters and a 33 kernel. After that, max-pooling layers are applied to the output of these convolutional layers to minimize the spatial dimensions of the feature maps.

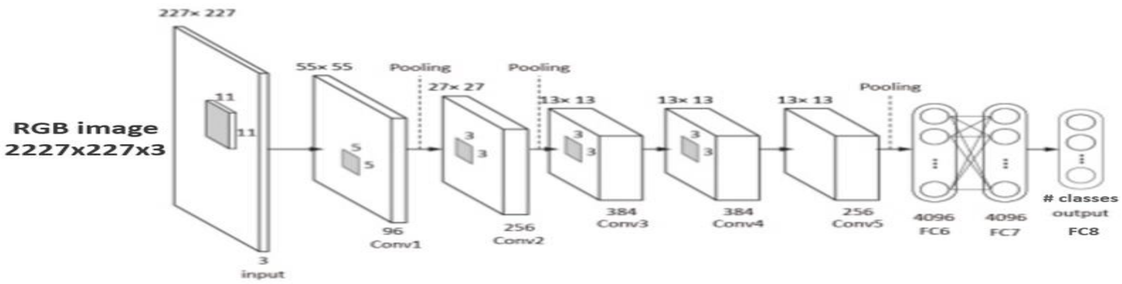


Figure 5.7 AlextNet

On September 30, 2012, AlexNet participated in the ImageNet Large Scale Visual Recognition Challenge. The network outperformed the runner-up by more than 10.8 percentage points with a top-5 error of 15.3%. The main finding of the original research was that the depth of the model, which was computationally expensive but made possible by the use of graphics processing units (GPUs) during training, was crucial for its high performance. The initial five layers of AlexNet were convolutional, part of them were followed by max-pooling layers, and the final three layers were fully connected. All layers up to the last are divided into two copies, each of which is run on a different GPU. The full framework can be expressed as:

$$(CNN \rightarrow RN \rightarrow MP)^2 \rightarrow (CNN^3 \rightarrow MP) \rightarrow (FC \rightarrow DO)^2 \rightarrow Linear \rightarrow softmax$$

where,

- CNN = convolutional layer (with ReLU activation)
- RN = local response normalization
- MP = maxpooling
- FC = fully connected layer (with ReLU activation)
- Linear = fully connected layer (without activation)
- DO = dropout

It used the non-saturating ReLU activation function, which showed improved training performance over tanh and sigmoid.

5.5 Performance Metrics

Several performance metrics are available to assess the effectiveness of reversible watermarking techniques for natural images. One of the crucial phases in creating a successful machine learning model is evaluating its performance. Different metrics—also referred to as performance metrics or evaluation metrics—are used to assess the effectiveness or quality of the model. These performance indicators enable us to evaluate how well our model handled the supplied data. By adjusting the hyper-parameters, we can make the model perform better. Each ML model aspires to generalize well on new or previously unexplored data and performance metrics help assess the model's success in this regard**.**

5.5.1Image quality metrics

Full-reference algorithms compare the input image against a pristine reference image with no distortion. No-reference algorithms compare statistical features of the input image against a model trained with a large database of naturally acquired images. The metrics are PSNR (Peak Signal to Noise Ratio), SNR, MSE (Mean Square Error), SSIM, BRIQUE and NIQE to analyses the quality of the image.

5.5.1 Accuracy

The sum of true positives and true negatives divided by the total number of samples. This is only accurate if the model is balanced. Accuracy is then given as the number of correct predictions divided by the total number of predictions.

$$\text{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN} + \mathrm{TN}}$$

5.5.2 Precision

Precision is the ability of a classifier not to label an instance positive that is actually negative. For each class, it is defined as the ratio of true positives to the sum of a true positive and false positive. It can be defined as the number of correct outputs provided by the model or out of all positive classes that have predicted correctly by the model, how many of them were actually true. It can be calculated using the below formula:

$$\text{Precision}= \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$$

5.5.3 Recall

Recall is a measure of the classifier's completeness; the ability of a classifier to correctly find all positive instances. For each class, it is defined as the ratio of true positives to the sum of true positives and false negatives. It is defined as the out of total positive classes, how our model predicted correctly. The recall must be as high as possible.

$$\text{Recall}= \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$$

5.5.4 F-measure

If two models have low precision and high recall or vice versa, it is difficult to compare these models. So, for this purpose, use F-score. This score helps us to evaluate the recall and precision at the same time. The F-score is maximum if the recall is equal to the precision. ss can be calculated using the below formula:

$$\text{F-measure}= \frac{2*\text{Recall}*\text{Precision}}{\text{Recall}+\text{Precision}}$$

5.5.5 AUC Curve

The Area Under the Curve (AUC) is the measure of the ability of a binary classifier to distinguish between classes and is used as a summary of the ROC curve. It is calculated by adding Concordance Percent and 0.5 times of Tied Percent. That is, AUC measures the entire two-dimensional area underneath the entire ROC curve (think integral calculus) from (0,0) to (1,1). It provides an aggregate measure of performance across all possible classification thresholds. ROC probability curve and AUC represents the degree or measure of separability.

6. Experimental Result

Various classification techniques were used on the publicly accessible dataset. Comparing the effectiveness of various classification algorithms, including CNN, DBN, LSTM, and Bi-LSTM, as well as the suggested approach utilizing digitalized photographs of the disease, is part of the dataset. Only Alzheimer images that were downloaded from various websites were used to test the implementation algorithms. Experimental results are evaluated using subjective studies.

Figure showing the results of performance metrics analysis and AD detection and diagnosis procedures. Using classification, the Alzheimer of the neurons and tissues from the digitized stained AD are extracted. This research work has compared the effectiveness of classification algorithms like CNN, DBN, LSTM, and Bi-LSTM using digitized Alzheimer disease images that are included in the dataset using a set of images of Alzheimer disease that were gathered from a publicly accessible database called Alzheimer dataset.

6.1 Segmentation using Fuzzy C-Means Clustering

Figure 6.1 Alzheimer Segmented Image using Fuzzy C-Means Clustering.

Table 6.1 Performance Metrics of the Alzheimer dataset Using Fuzzy C-Means Clustering

Target Class	PSNR	SNR	MSE	SSIM	BRIQUE		NIQE	
					Original	Noisy	Original	Noisy
Mild Demented	11.47	10.35	12.93	6.70	10.35	11.45	14.86	15.91
Moderate Demented	10. 35	9. 63	11. 89	8. 93	11. 40	13. 81	10. 73	16. 53
Non-Demented	12.56	11.84	10.05	7.76	12.40	12.93	12.73	14.90
Very Mild Demented	10.52	10.40	13.85	8.70	11.35	11.41	11.86	13.74

6.2 Segmentation using K-Means Clustering

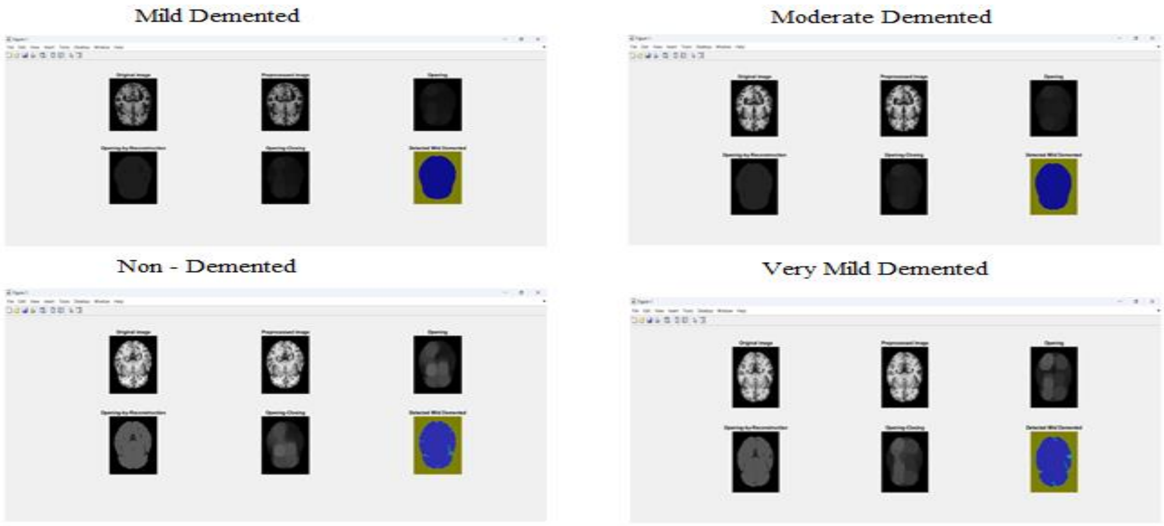


Figure 6.2 Alzheimer Segmented Image using K-Means Clustering.

Table 6.2 Performance Metrics of the Alzheimer dataset Using K-Means Clustering

Target Class	PSNR	SNR	MSE	SSIM	BRIQUE		NIQE	
					Original	Noisy	Original	Noisy
Mild Demented	3.47	2.35	2.93	6.70	1.35	1.45	4.86	5.91
Moderate Demented	4. 35	5. 63	1. 89	8. 93	1. 40	3. 81	5. 73	6. 53
Non-Demented	2.56	3.84	1.05	7.76	2.40	2.93	2.73	4.90
Very Mild Demented	5.52	3.40	3.85	8.70	3.35	2.41	3.86	3.74

6.3 Watershed Segmentation using Gradients

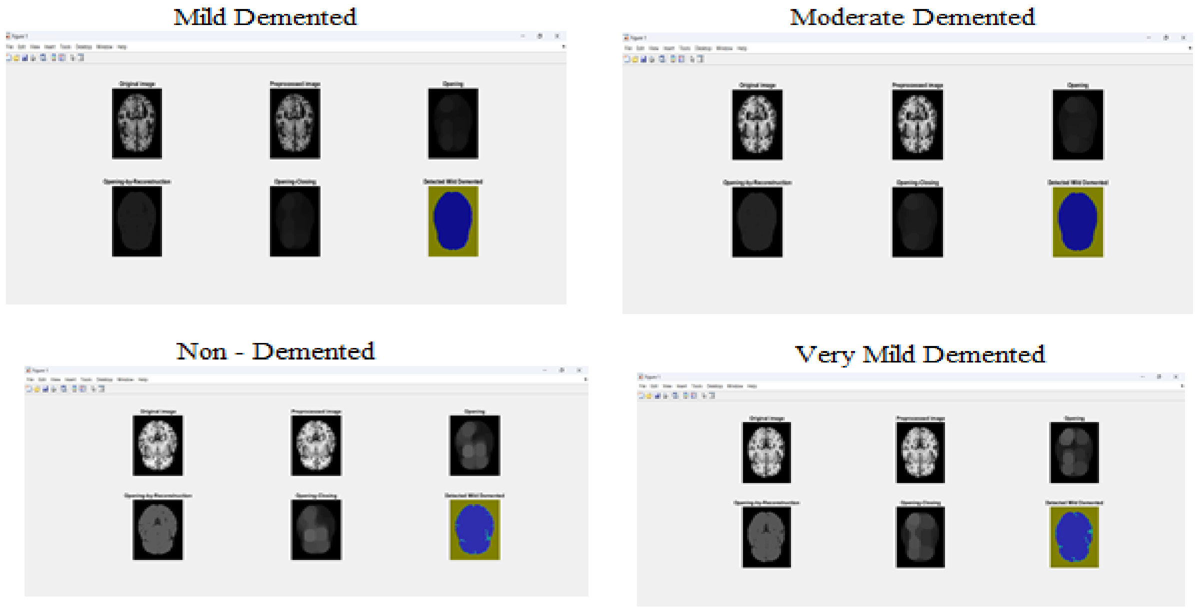


Figure 6.3 Alzheimer Segmented Image Using Watershed with Gradients.

Table 6.3 Performance Metrics of the Alzheimer dataset Using Watershed with Gradients

Target Class	PSNR	SNR	MSE	SSIM	BRIQUE		NIQE	
					Original	Noisy	Original	Noisy
Mild Demented	6.02	6.05	6.12	6.15	6.18	6.21	6.25	6.30
Moderate Demented	6.38	6.22	6.28	6.32	6.35	6.37	6.41	6.43
Non-Demented	7.32	7.02	7.25	7.44	7.45	7.35	7.39	7.48
Very Mild Demented	7.45	7.52	7.54	7.56	7.57	7.58	7.45	7.59

For model development and evaluation, our data set was divided into a train/test split with a ratio of 11/1 without any overlap. Therefore, 12,554 images (41% blacklegged) were used for the training set, and 1034 (41% blacklegged) were used for the test set to validate the performance of the developed model.

Table 6.4 Performance Metrics of the Alzheimer dataset using four different deep learning classifiers

Method	CNN	LSTM	BILSTM	DBN
Accuracy	85	68	70	69
Sensitivity	82	70	68	67
Specificity	85	65	62	70
F-Measure	86	50	68	70
AUC	81	63	70	70.3

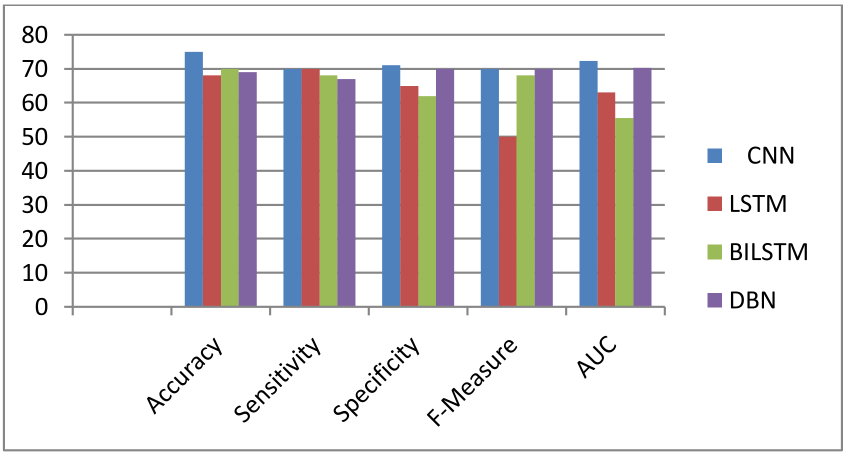
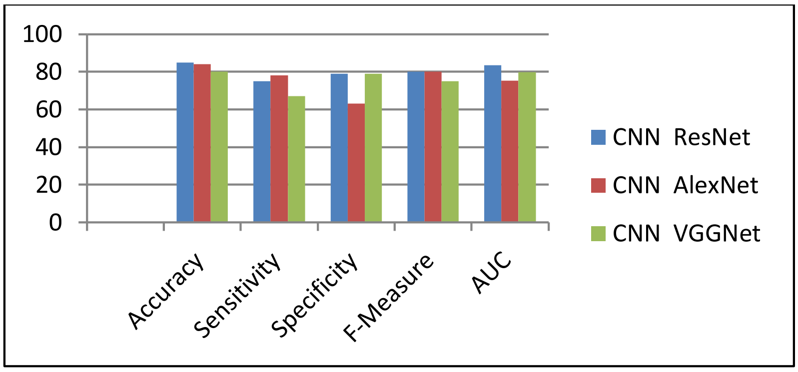


Table 6.5 Performance Metrics of the Alzheimer dataset Using CNN classifiers with Transfer Learning

	CNN		
Method	**ResNet**	**AlexNet**	**VGGNet**
Accuracy	95	84	90
Sensitivity	94	88	89
Specificity	96	85	91
F-Measure	94	80	92
AUC	93	82	90



7. CONCLUSION

The primary objective of this research is to use MRI pictures of patients to detect and diagnose Alzheimer's disease early and treat patients. Pre-processing, segmentation, and deep learning techniques are employed in this work. The tumor is segmented using techniques like Fuzzy Means Clustering, Kmeans Clustering, and the Watershed algorithm, and then it is classified using deep learning classification algorithms like CNN, DBN, LSTM, and BiLSTM, with CNN providing the highest level of accuracy. The classification was then redone using the Transfer Learning technique, which includes ResNet, VGGNet, and AlexNet. ResNet performed more accurately than the initial classification. The Evolutionary Algorithm was employed to improve performance, and it also speeds up the process and increases accuracy.

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